APPENDIX E: FEATURE DEFINITIONS

The principle goal of the feature generation process (described in Section 4) is to produce features that are indicative of incident conditions. This appendix identifies several candidate traffic features. In general, these features are based on intuitive and/or theoretical arguments that suggest a correlation between certain feature values and incident-related traffic conditions. The simplest feature of this type is the raw surveillance data itself, which can be viewed as a baseline feature set in order to judge the relative effectiveness of other candidate features. The following sections identify the candidate feature sets explicitly.

E.1 Features from the California Algorithm

All features from the California algorithms are defined in terms of the following measurement data.

OCC(i, 0, t)	The one-minute occupancy, expressed as a percent, at station i, time t, averaged across all lanes.
OCC(i, j, t)	The one-minute occupancy, expressed as a percent, at station i, lane j, and time t.
VOL(i, 0, t)	The one-minute volume, expressed as a percent, at station i, time t, averaged across all lanes.
VOL(i, j, t)	The one-minute volume, expressed as a percent, at station i, lane j, and time t.

Features from the California algorithm are defined below. The G-factor appearing in these definitions is empirically determined so that speed estimates are in miles per hour (the California algorithm employed a default value of 2.86 as determined from Los Angeles surveillance data).

Table E-1. Features Used in the California Algorithms

Name	Description	Definition
DOCC(i, t)	Downstream occupancy	OCC(i+1, 0, t)
OCCDF(i, t)	Spatial occupancy difference	OCC(i, 0, t) - OCC(i+1, 0, t)
OCCRDF(i, t)	Relative spatial occupancy difference.	OCCDF(i, t) / OCC(i, 0, t)
DOCCTD(i, t)	Relative temporal difference in downstream occupancy.	[OCC(i+1, 0, t-2) - OCC(i+1, 0, t)] / OCC(i+1, 0, t-2)
SPD(i, t)	Speed	VOL(i, 0, t) / [OCC(i, 0, t) x G]
SPDTDF(i, t)	Relative temporal difference in speed.	[SPD(i, t-2)-SPD(i, t)] / SPD(i, t-2)
OCCL5	Five-minute average lane- specific occupancy.	$(1/5) \sum_{k=0}^{4}$ OCC(i, j, t-k)
VOLL5	Five-minute average lane- specific volume.	$(1/5) \sum_{k=0}^{4}$ VOL(i, j, t-k)
SPDL5	Five-minute average lane- specific speed.	VOLL5(i, j, t) / [OCCL5(i, j, t) x G]
OCCL5	Five-minute average occupancy	$(1/5) \sum_{k=0}^{4}$ OCC(i, 0, t-k)

E.2 Features from the McMaster Algorithm

The McMaster algorithm detects incidents in two stages: (1) detect the existence of congestion, and (2) determine the cause of congestion. Both steps are accomplished using a volume/occupancy template that must be calibrated for each detector station in the surveillance network. A sample template is shown in Figure E-1.

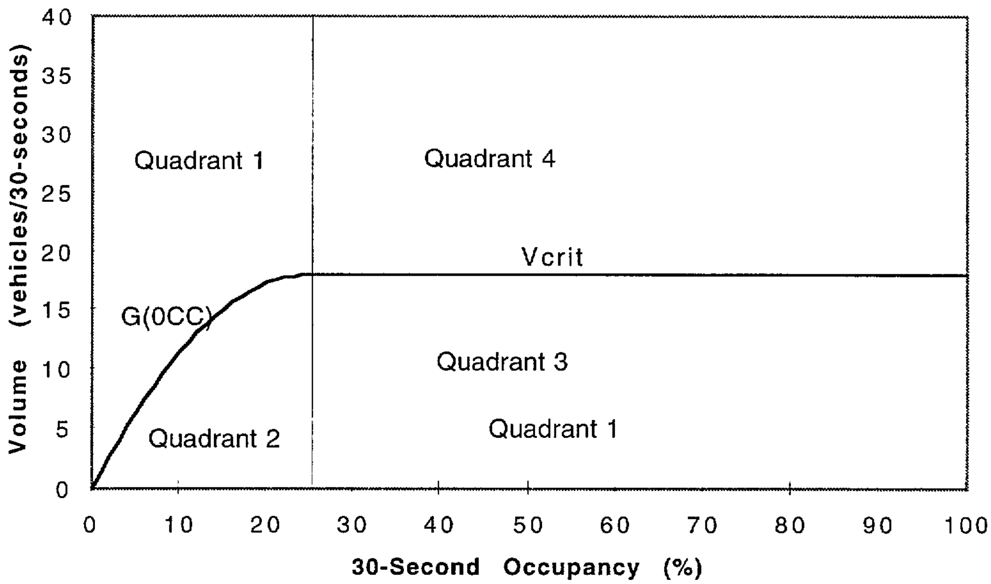

Figure E-1. The Volume/Occupancy Template from the McMaster Algorithm

In the figure, the volume/occupancy plane is divided into four quadrants. The quadrant boundaries V_{crit}, OCMAX and G(OCC) are calibrated from historical measurement data as described at the end of this subsection.

At any given station, congestion is detected either when speeds are excessively slow or traffic operations are in quadrants 2 or 3, which represent low volumes for the given occupancy. Once congestion is detected, the cause of congestion is determined using measurements from the adjacent downstream station.

At the downstream station, the following logic is used to determine the cause of congestion. Traffic operations in quadrants 1 or 2 indicate that the cause of congestion is a capacity-reducing incident. Traffic operations in quadrant 4 indicate that the congestion is "recurrent" and resulted from excess traffic demand. Traffic operations in quadrant 3 indicate that the cause of congestion is farther downstream, and the next downstream station is used to determine the cause of congestion.

Certain features have been derived from this logic that allow a binary decision tree classifier to reproduce the McMaster algorithm. These are defined below:

X - 1 if speed is low or traffic is in quadrants 2 or 3
0 otherwise

Y - 0 if traffic is in quadrant 4
1 if traffic is in quadrants 1 or 2
2 if traffic is in quadrant 3

It is not expected that the DCo module of the operational algorithm will utilize these features to implement the McMaster algorithm. Rather, these features are to be used in the construction of empirically derived classifiers whose performance will be evaluated relative to other classification schemes.

Calibration of the Volume Occupancy Templates

The following procedure was followed to determine the quadrant boundaries of the station-specific volume/occupancy templates employed in the McMaster algorithm (see [GALL 89] and [PERS 89]). The function G(OCC), which defines the minimum uncongested volume threshold in Figure E- 1, is defined as:

$$G(OCC) = k * F(OCC) \quad \text{for,} \quad (0 < k < 1)$$

where,

$$F(OCC) = B * OCC” + E$$

for model parameters A and B and error term E. Since the assumed model is non-linear, non-linear estimation techniques must be employed in order to estimate the model parameters. This is done by using volume-occupancy data collected under uncongested traffic conditions.

In the original algorithm, a visual inspection of the data indicated that an OCMAX value of 25% was appropriate. A non-linear parameter estimation program was then employed to determine values of A and B such that the resulting F(OCC) was a reasonable estimate of the observed uncongested volume-occupancy data. The value of k was then determined so that G(OCC) would be a lower bound for 95% of all volumes observed at a given occupancy value. Different parameter values were determined for each of the selected detector stations, but, in general, k was taken to be approximately 0.8, A was taken to be between 0.8 1 and 0.85, and B was taken to be between 1.6 and 2.5.

E.3 Features Based on Traffic Stream Correlation

The features described in this section are based on the premise that traffic measurements from adjacent detector stations are correlated. Specifically, in light traffic conditions, a relatively strong correlation can be observed between the traffic pattern at an upstream station and the resulting downstream traffic pattern after an appropriate time lag. This correlation becomes weaker as traffic demand and sensor spacing increases.

Since the traffic data is correlated, measurements from an upstream station can be used to estimate subsequent downstream measurements based on certain statistical considerations. By observing large errors in this measurement "forecasting" scheme, one may infer the existence of an incident.

The theoretical basis of this approach is addressed below.

Upstream-Downstream Correlation Analvsis

We consider two time series, x(k) and y(k), corresponding to traffic data from adjacent upstream and downstream detector stations, respectively. As the theory suggests a correlation of fluctuations, it is appropriate to consider deviations of these traffic variables from their trends:

$$i(k) = x(k) - t,(k) \qquad (E.1)$$

$$y(k) = y(k) - 1, (k) \qquad (E.2)$$

Determination of the trends, tx(k) and ty(k), is deferred to the next subsection.

It is expected that the values of $y(k)$ can be predicted from past values of $j;(k)$. The problem we address at this point is the determination of those coefficients, a(nlk), n=n0, ... n 1, which provide the best estimates,

$$\hat{\tilde{y}}(k-m|k)=\sum_{n=n_0}^{n_1}a(n|k)\tilde{x}(k-m-n) \qquad ,m=0,1,\ldots \tag{E.3}$$

in the sense that the error,

$$E(k)=\sum_{m=0}^{\infty}e^{-m\alpha}[\tilde{y}(k-m)-\hat{\tilde{y}}(k-m|k)]^2 \tag{E.4}$$

is minimized. This approach is chosen, in part, because of the computational convenience which results.

Straightforward computations yield the following equations for the correlation coefficients:

$$\sum_{q=n_0}^{n_1}a(q|k)\sigma_{xx}(n,q|k)=\sigma_{yx}(n|k) \qquad ,n=n_0,\ldots,n_1 \tag{E.5}$$

where,

$$\sigma_{xx}(n,q|k)=\sum_{m=0}^{\infty}e^{-m\alpha}\tilde{x}(k-m-n)\tilde{x}(k-m-q) \tag{E.6}$$

and,

$$\sigma_{yx}(n,|k)=\sum_{m=0}^{\infty}e^{-m\alpha}\tilde{y}(k-m-q)\tilde{x}(k-m-n) \tag{E.7}$$

Computational convenience arises from the fact that the required quantities can be computed recursively:

$$\sigma_{xx}(n,q|k+1)=e^{-\alpha}\sigma_{xx}(n,q|k)+\tilde{x}(k+1-n)\tilde{x}(k+1-q) \tag{E.8}$$

$$\sigma_{yx}(n|k+1)=e^{-\alpha}\sigma_{yx}(n|k)+\tilde{y}(k+1)\tilde{x}(k+1-n) \tag{E.9}$$

Further, from (6) it can be seen that

$$\sigma_{xx}(n+1,q+1|k+1)=\sigma_{xx}(n,q|k) \tag{E.10}$$

Therefore, equation (10) can be employed for $n=n_0, \ldots, n_1$ and $q=n_0, \ldots, n_1$ to obtain most of the elements of $\sigma_{xx}(n,q|k+1)$. Finally, we note the symmetry of this array, i.e.,

$$\sigma_{xx}(n,q|k)=\sigma_{xx}(q,n|k) \tag{E.11}$$

so that (8) need only be used to compute $\sigma_{xx}(n_0,q|k+1)$ for $q=n_0, \ldots, n_1$. Symmetry can also be exploited to reduce storage requirements. One can show that,

$$E(k)=\sigma_{yy}(0,0,k)-\sum_{n=n_0}^{n_1}a(n|k)\sum_{q=q_0}^{n_1}a(q|k)\sigma_{xx}(n,q|k) \tag{E.12}$$

where,

$$\sigma_{yy}(n,q|k)\equiv\sum_{m=0}^{n_1}e^{-m\alpha}\tilde{y}(k-m-n)\tilde{y}(k-m-q) \tag{E.13}$$

Computation of the Trend

We have found that σ_{xx}, etc., are determined by recursive, single exponential smoothing relations. To be consistent with this, the trend values are also determined from exponential smoothing. Thus we compute,

$$s_x^{(1)}(k+1)=e^{-\alpha}s_x^{(1)}(k)+(1-e^{-\alpha})x(k+1) \tag{E.14}$$

and compute the trend values as,

$$t_x(k+1)=s_x^{(1)}(k) \tag{E.15}$$

with identical relations for the downstream variable obtained by replacing x with y.

When trends are present in the traffic data, it may be desirable to account for this by employing higher-order exponential smoothing. For example, to account for a straight-line trend, one can employ double exponential smoothing as follows:

$$s_x^{(1)}(k+1) = e^{-\alpha} s_x^{(1)}(k) + (1 - e^{-\alpha}) x(k+1) \tag{E.16}$$

$$s_x^{(2)}(k+1) = e^{-\alpha} s_x^{(2)}(k) + (1 - e^{-\alpha}) s_x^{(1)}(k+1) \tag{E.17}$$

The trend values are then taken as one-step forecasts:

$$t_x(k+1) = 2 s_x^{(1)}(k) - s_x^{(1)}(k) + [e^{-\alpha} - 1][s_x^{(1)}(k) - s_x^{(2)}(k)] \tag{E.18}$$

<u>Generalized Correlation Analysis</u>

The analysis of the previous two subsections apply more generally to y(k) considered to be a dependent time series and to x(k), an independent time series. For example, in congested traffic, fluctuations move in an upstream direction so that one could take y(k) to correspond to the upstream station and x(k) to correspond to the downstream station. As a second example, in certain locations where on-ramp traffic is particularly heavy, one might wish to relate observed fluctuations in main-line occupancy (y) to fluctuations in the on-ramp volume (x).

In the situation of the latter example, an even better forecasting might be obtained by using two independent time series, e.g., upstream occupancy and on-ramp volume. To handle this, a generalization of the previous development is taken up here.

As before, $\tilde{y}(k)$ is the time series of deviations from the trend of the dependent time series. Now we can consider a vector time series,

$$x(k) = \begin{bmatrix} x_1(k) \\ \vdots \\ x_p(k) \end{bmatrix} \tag{E.19}$$

i.e., a collection of p independent time series. Trends for each component can be separately computed,

$$t_x(k) = \begin{bmatrix} t_{x_1}(k) \\ \vdots \\ t_{x_p}(k) \end{bmatrix} \tag{E.20}$$

and then a vector of deviations,

$$\tilde{x}(k) = \begin{bmatrix} x_1(k) - t_{x_1}(k) \\ \vdots \\ x_p(k) - t_{x_p}(k) \end{bmatrix} \tag{E.21}$$

can be identified. The optimal forecast problem is then the determination of the array of coefficients,

$$a(n|k) = \begin{bmatrix} a_1(n|k) \\ \vdots \\ a_p(n|k) \end{bmatrix} \qquad ,n = n_0,\ldots,n_1 \tag{E.22}$$

which provide the best estimates,

$$\hat{\tilde{y}}(k-m) = \sum_{n=n_0}^{n_1} \sum_{r=1}^{p} a_r(n|k)\tilde{x}_r(k-m-n) \tag{E.23}$$

in the sense that the error,

$$E(k) = \sum_{m=0}^{\infty} e^{-m\alpha}[\tilde{y}(k-m) - \hat{\tilde{y}}(k-m|k)]^2 \tag{E.24}$$

is minimized. To identify equations defining a(n|k), we first define the following quantities:

$$\sigma_{yy}(n,q|k) = \sum_{m=0}^{\infty} e^{-m\alpha} \tilde{y}(k-m-n)\tilde{y}(k-m-q) \tag{E.25}$$

$$\sigma_{yx_j}(n|k) = \sum_{m=0}^{\infty} e^{-m\alpha} \tilde{y}(k-m)\tilde{x}_j(k-m-n) \tag{E.26}$$

$$\sigma_{x_i x_j}(n,q|k) = \sum_{m=0}^{\infty} e^{-m\alpha} \tilde{x}_i(k-m-n)\tilde{x}_j(k-m-q) \tag{E.27}$$

Now, inserting (23) into (24), we have

$$E(k) = \sum_{m=0}^{\infty} e^{-m\alpha} [\tilde{y}(k-m) - \sum_{n=n_0}^{n_1} \sum_{r=1}^{p} a_r(n|k)\tilde{x}_r(k-m-n)]^2$$

$$E(k) = \sum_{m=0}^{\infty} e^{-m\alpha} [y(k-m)]^2 - 2\sum_{n=n_0}^{n_1} \sum_{r=1}^{p} a_r(n|k) \sum_{m=0}^{\infty} e^{-m\alpha} \tilde{y}(k-m)\tilde{x}_r(k-m-n)$$
$$+ \sum_{n=n_0}^{n1} \sum_{q=n_0}^{n_1} \sum_{r=1}^{p} \sum_{s=1}^{p} a_r(n|k)a_s(q|k) \sum_{m=0}^{\infty} e^{-m\alpha} \tilde{x}_r(k-m-n)\tilde{x}_s(k-m-q)$$

$$\begin{aligned} E(k) &= \sigma_{xx}(0,0|k) - 2\sum_{n=n_0}^{n_1} \sum_{r=1}^{p} a_r(n|k)\sigma_{yx_r}(n,q|k) \\ &+ \sum_{n=n_0}^{n_1} \sum_{q=n_0}^{n_1} \sum_{r=1}^{p} \sum_{s=1}^{p} a_r(n|k)a_s(n|k)\sigma_{x_r x_s}(n,q|k) \end{aligned} \tag{E.28}$$

Let,

$$A = \begin{bmatrix} a_1(n_0|k) \\ \vdots \\ a_1(n_1|k) \\ \vdots \\ a_p(n_0|k) \\ \vdots \\ a_p(n_1|k) \end{bmatrix} \tag{E.29}$$

$$\sigma_{yx} = \begin{bmatrix} \sigma_{yx_1}(n_0) \\ \vdots \\ \sigma_{yx_1}(n_1) \\ \vdots \\ \sigma_{yx_p}(n_0) \\ \vdots \\ \sigma_{yx_p}(n_1) \end{bmatrix} \tag{E.30}$$

$$\sigma_{x_i x_j} = \begin{bmatrix} \sigma_{x_i x_j}(n_0, n_0), & \cdots, & \sigma_{x_i x_j}(n_0, n_1) \\ \vdots & & \\ \sigma_{x_i x_j}(n_1, n_0), & \cdots, & \sigma_{x_i x_j}(n_1, n_1) \end{bmatrix} \tag{E.31}$$

$$\sigma_{xx} = \begin{bmatrix} \sigma_{x_1 x_1}, & \cdots, & \sigma_{x_1 x_p} \\ \sigma_{x_p x_1}, & \cdots, & \sigma_{x_p x_p} \end{bmatrix} \tag{E.32}$$

Then, using vector-matrix notation,

$$E(k) = \sigma_{yy}(0,0|k) - 2A'\sigma_{yx} + A'\sigma_{xx}A \tag{E.33}$$

and,

$$E(k) = \sigma_{yy}(0,0|k) - \sigma'_{yx}\sigma_{xx}^{-1}\sigma_{yx} + [\sigma_{xx}A - \sigma_{yx}]'\sigma_{xx}^{-1}[\sigma_{xx}A - \sigma_{yx}] \tag{E.34}$$

As the last term is the only one involving A and is clearly nonnegative, the best choice of A is seen to be specified by,

$$\sigma_{xx}A = \sigma_{yx} \tag{E.35}$$

and, for this choice,

$$E(k) = \sigma_{yy}(0,0|k) - \sigma_{yx}^{t}\sigma_{xx}^{-1}\sigma_{yx} \quad \text{(E.36)}$$

Definition of Correlation Features

Based on the discussion of the previous subsections, the forecast of the dependent traffic variable is defined as the sum of a trend forecast and a fluctuation forecast:

$$\hat{y}(k+1) = t(k+1) + f(k+1) \quad \text{(E.37)}$$

where the trend forecast is defined by equation (15) if single exponential smoothing is used and by (18) if double exponential smoothing is used. The fluctuation forecast is given by:

$$f(k+1) = \sum_{n=n_0}^{n_1} a(n|k)\tilde{x}(k+1-n) \quad \text{(E.38)}$$

if a single independent time series is used and by equation (E.23) if more than one such series is used. An accumulated forecasting error is defined as:

$$e(k+1) = \theta_1 e(k) + \theta_2[y(k+1) - \hat{y}(k+1)] \quad \text{(E.39)}$$

with $\theta_1 \geq 0, \theta_2 \geq 0$. To obtain a normalization of the accumulated forecasting error, we define the smoothed mean absolute deviation:

$$\mu(k+1) = (1-\gamma)\mu(k) + \gamma|y(k+1) - \hat{y}(k+1)| \quad \text{(E.40)}$$

and then the normalized forecast error is given as follows:

$$\bar{e}(k+1) = e(k+1) / \mu(k) \quad \text{(E.41)}$$

It is expected that the normalized forecast error will prove an effective traffic feature since it measures the disparity between the observed downstream measurement data and the forecast data. Specifically, a large error can be viewed as an indication of incident conditions.

In addition, a feature which quantifies the correlation between the upstream and downstream data may prove useful. Specifically, such a feature could be computed as the following ratio:

$$\frac{\sigma_{yx}}{\sigma_{xx}\sigma_{yy}} \qquad \text{(E.42)}$$

The features identified in equations (41) and (42) warrant investigation for possible use in the Feature Generation component of the operational algorithm. These features may be evaluated both as station averages and, where data is sufficiently available, as single-lane values.

E.4 Additional Traffic Engineering Features

This section presents definitions of the traffic features utilized in algorithm development. In general, each feature is defined for measurement aggregation intervals of 30 seconds, one minute and five minutes. All features are defined in terms of station volume and occupancy measurements. Station occupancy is defined as the average occupancy of the station's constituent sensors. Station volume is defined as the average volume of the station's constituent sensors.

The feature definitions are given below. Features are listed alphabetically by the variable name used in RIDE, an expansion of the acronym, and a brief definition of the feature value.

Table E-2. Features Implemented in RIDE

Name	**Decsription**	**Definition**
DOCCTD1	Downstream Occupancy Temporal Difference (1-Min)	1.0 - (OCCDN1[t] / OCCDN1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
DLODF0	Downstream Lane Occupancy	DLORT0 = DLOMX0 -

Name	Decsription	Definition
	Difference (30-Sec)	DLOMNO
DLODFl	Downstream Lane Occupancy Difference (1 -Min)	DLORTI = DLOMXl- DLOMN 1
DLODF5	Downstream Lane Occupancy Difference (5-Min)	DLORTS = DLOMXS - DLOMNS
DLOMN0	Downstream Lane Occupancy Maximum (30-Sec)	Minimum occupancy of station's constituent sensors over the last 30 seconds
DLOMN 1	Downstream Lane Occupancy Maximum (1 -Min)	Minimum occupancy of station's constituent sensors over the last 1 minute
DLOMN5	Downstream Lane Occupancy Maximum (5-Min)	Minimum occupancy of station's constituent sensors over the last 5 minutes
DLOMX0	Downstream Lane Occupancy Minimum (30-Sec)	Maximum occupancy of station's constituent sensors over the last 30 seconds
DLOMX 1	Downstream Lane Occupancy Minimum (1 -Min)	Maximum occupancy of station's constituent sensors over the last 1 minute
DLOMX5	Downstream Lane Occupancy Minimum (1-Min)	Maximum occupancy of station's constituent sensors over the last 5 minutes
DLORTO	Downstream Lane Occupancy Ratio (30-Sec)	DLORTO = DLOMXO / DLOMNO
DLORT 1	Downstream Lane Occupancy Ratio (I-Min)	DLORTl = DLOMXl / DLOMN 1
DLORT5	Downstream Lane Occupancy Ratio (5-Min)	DLORT5 = DLOMX5 / DLOMN5
DLSDF0	Downstream Lane Speed Difference (30-Sec)	DLSDFO = DLSMXO - DLSMNO
DLSDFl	Downstream Lane Speed Difference (1 -Min)	DLSDFl = DLSMXl - DLSMN 1
DLSDF5	Downstream Lane Speed Difference (5-Min)	DLSDF5 = DLSMX5 - DLSMN5
DLSMN0	Downstream Lane Speed Minimum (30-Sec)	Minimum speed of station's constituent sensors over the last 30 seconds
DLSMN 1	Downstream Lane Speed Minimum (1 -Min)	Minimum speed of station's constituent sensors over the last 1 minute
DLS MN5	Downstream Lane Speed Minimum (5-Min)	Minimum speed of station's constituent sensors over the last

Name	Decsription	Definition
		I 5 minutes
DLSMX0	Downstream Lane Speed Maximum (30-Sec)	Maximum speed of station's constituent sensors over the last 30 seconds
DLSMXl	Downstream Lane Speed Maximum (1 -Min)	Maximum speed of station's constituent sensors over the last 1 minute
DLSMX5	Downstream Lane Speed Maximum (5-Min)	Maximum speed of station's constituent sensors over the last 5 minute
DLSRT0	Downstream Lane Speed Ratio (30-Sec)	DLSRTO = DLSMXO / DLSMNO
DLSRT 1	Downstream Lane Speed Ratio (l-Min)	DLSRTI = DLSMXl / DLSMN 1
DLSRT5	Downstream Lane Speed Ratio (5-Min)	DLSRT5 = DLSMX5 / DLSMN5
DLVDF0	Downstream Lane Volume Difference (30-Sec)	DLVDFO = DLVMXO - DLVMNO
DLVDFl	Downstream Lane Volume Difference (1 -Min)	DLVDFl = DLVMXl- DLVMN 1
DLVDF5	Downstream Lane Volume Difference (5-Min)	DLVDF5 = DLVMX5 - DLVMN5
DLVMNO	Downstream Lane Volume Minimum (30-Sec)	Minimum volume of station's constituent sensors over the last 30 seconds
DLVMN 1	Downstream Lane Volume Minimum (1-Min)	Minimum volume of station's constituent sensors over the last 1 minute
DLVMN5	Downstream Lane Volume Minimum (55-Min)	Minimum volume of station's constituent sensors over the last 5 minutes
DLVMXO	Downstream Lane Volume Maximum (30-Sec)	Maximum volume of station's constituent sensors over the last 30 seconds
DLVMX 1	Downstream Lane Volume Maximum (1 -Min)	Maximum volume of station's constituent sensors over the last 1 minute
DLVMX5	Downstream Lane Volume Maximum (5-Min)	Maximum volume of station's constituent sensors over the last 5 minutes
DLVRTO	Downstream Lane Volume Ratio (30-Sec)	DLVRTO = DLVMXO / DLVMNO I

Name	Decsription	Definition
DLVRT1	Downstream Lane Volume Ratio (1-Min)	DLVRT1 = DLVMX1 / DLVMN1
DLVRT5	Downstream Lane Volume Ratio (5-Min)	DLVRT5 = DLVMX5 / DLVMN5
DODDT1	Downstream Occupancy First Derivative (1-Min)	Rate of change in OCCDN1 over last 1 minute
DOD2DT1	Downstream Occupancy Second Derivative (1-Min)	Rate of change in DODDT1 over last 1 minute
DSPDTD1	Downstream Speed Temporal Difference (1-Min)	1.0 - (SPDDN1[t] / SPDDN1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
DVDDT1	Downstream Volume First Derivative (1-Min)	Rate of change in VOLDN1 over last 1 minute
DVD2DT1	Downstream Volume Second Derivative (1-Min)	Rate of change in DVDDT1 over last 1 minute
DVOLTD1	Downstream Volume Temporal Difference (1-Min)	1.0 - (VOLDN1[t] / VOLDN1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
MCMSTRX	McMaster Feature - Variable X	Defined in Section E.2
MCMSTRY	McMaster Feature - Variable Y	Defined in Section E.2
OCCDN0	Occupancy Downstream (30-Sec)	Average occupancy over 30-second period
OCCDN1	Occupancy Downstream (1-Min)	Average occupancy over 1-minute period
OCCDN5	Occupancy Downstream (5-Min)	Average occupancy over 5-minute period
OCCFDN0	Occupancy Filtered Downstream (1-Min)	Kalman filtered value of OCCDN0
OCCFUP0	Occupancy Filtered Upstream (1-Min)	Kalman filtered value of OCCUP0
OCCSDF0	Occupancy Spatial Difference (30-Sec)	OCCSDF0 = OCCUP0 - OCCDN0
OCCSDF1	Occupancy Spatial Difference (1-Min)	OCCSDF1 = OCCUP1 - OCCDN1
OCCSDF5	Occupancy Spatial Difference (5-Min)	OCCSDF0 = OCCUP5 - OCCDN5
OCCSDR0	Occupancy Spatial Difference	OCCSDR0 = OCCSDF0 /

Name	Decsription	Definition
	Relative (30-Sec)	OCCUP0
OCCSDR1	Occupancy Spatial Difference Relative (1-Min)	OCCSDR1 = OCCSDF1 / OCCUP1
OCCSDR5	Occupancy Spatial Difference Relative (5-Min)	OCCSDR5 = OCCSDF5 / OCCUP5
OCCSRT0	Occupancy Spatial Ratio (30-Sec)	OCCSRT0 = OCCUP0 / OCCDN0
OCCSRT1	Occupancy Spatial Ratio (1-Min)	OCCSRT1 = OCCUP1 / OCCDN1
OCCSRT5	Occupancy Spatial Ratio (5-Min)	OCCSRT5 = OCCUP5 / OCCDN5
OCCUP0	Occupancy Upstream (30-Sec)	Average occupancy over 30-second period
OCCUP1	Occupancy Upstream (1-Min)	Average occupancy over 1-minute period
OCCUP5	Occupancy Upstream (5-Min)	Average occupancy over 5-minute period
SPDDN0	Speed Downstream (30-Sec)	Average traffic speed at downstream detector station SPDDN0 = VOLDN0 / (G * OCCDN0)
SPDDN1	Speed Downstream (1-Min)	Average traffic speed at downstream detector station SPDDN1 = VOLDN1 / (G * OCCDN1)
SPDDN5	Speed Downstream (5-Min)	Average traffic speed at downstream detector station SPDDN5 = VOLDN5 / (G * OCCDN5)
SPDFDN0	Speed Filtered Downstream (1-Min)	Kalman filtered value of SPDDN0
SPDFUP0	Speed Filtered Upstream (1-Min)	Kalman filtered value of SPDUP0
SPDHP5	Speed Historical Probability (1-Min)	Estimated probability of speed increase - see Section 11.1.1
SPDSDF0	Speed Spatial Difference (30-Sec)	SPDSDF0 = SPDUP0 - SPDDN0
SPDSDF1	Speed Spatial Difference (1-Min)	SPDSDF1 = SPDUP1 - SPDDN1
SPDSDF5	Speed Spatial Difference (5-Min)	SPDSDF5 = SPDUP5 - SPDDN5

Name	Decsription	Definition
SPDSDR0	Speed Spatial Difference Relative (30-Sec)	SPDSDR0 = SPDSDF0 / SPDUP0
SPDSDR1	Speed Spatial Difference Relative (1-Min)	SPDSDR1 = SPDSDF1 / SPDUP1
SPDSDR5	Speed Spatial Difference Relative (5-Min)	SPDSDR5 = SPDSDF5 / SPDUP5
SPDSRT0	Speed Spatial Ratio (30-Sec)	SPDSRT0 = SPDUP0 / SPDDN0
SPDSRT1	Speed Spatial Ratio (1-Min)	SPDSRT1 = SPDUP1 / SPDDN1
SPDSRT5	Speed Spatial Ratio (5-Min)	SPDSRT5 = SPDUP5 / SPDDN5
SPDTDF	Upstream Speed Temporal Difference (1-Min)	1.0 - (SPDUP1[t] / SPDUP1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
SPDTDF0	Downstream Speed Temporal Difference (30-Sec)	1.0 - (SPDDN0[t] / SPDDN0[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
SPDTDF1	Downstream Speed Temporal Difference (1-Min)	1.0 - (SPDDN1[t] / SPDDN1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
SPDUP0	Speed Upstream (30-Sec)	Average traffic speed at upstream detector station SPDUP0 = VOLUP0 / (G * OCCUP0)
SPDUP1	Speed Upstream (1-Min)	Average traffic speed at upstream detector station SPDUP1 = VOLUP1 / (G * OCCUP1)
SPDUP5	Speed Upstream (5-Min)	Average traffic speed at upstream detector station SPDUP5 = VOLUP5 / (G * OCCUP5)
UOCCTD1	Upstream Occupancy Temporal Difference (1-Min)	1.0 - (OCCUP1[t] / OCCUP1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
ULODF0	Upstream Lane Occupancy Difference (30-Sec)	ULODF0 = ULOMX0 - ULOMN0
ULODF1	Upstream Lane Occupancy Difference (1-Min)	ULODF1 = ULOMX1 - ULOMN1

Name	**Decsription**	**Definition**
ULODF5	Upstream Lane Occupancy Difference (5-Min)	ULODF5 = ULOMX5 - ULOMN5
ULOMN0	Upstream Lane Occupancy Minimum (30-Sec)	Minimum occupancy of station's constituent sensors over the last 30 seconds
ULOMN1	Upstream Lane Occupancy Minimum (1-Min)	Minimum occupancy of station's constituent sensors over the last 1 minute
ULOMN5	Upstream Lane Occupancy Minimum (5-Min)	Minimum occupancy of station's constituent sensors over the last 5 minutes
ULOMX0	Upstream Lane Occupancy Maximum (30-Sec)	Maximum occupancy of station's constituent sensors over the last 30 seconds
ULOMX1	Upstream Lane Occupancy Maximum (1-Min)	Maximum occupancy of station's constituent sensors over the last 1 minute
ULOMX5	Upstream Lane Occupancy Maximum (5-Min)	Maximum occupancy of station's constituent sensors over the last 5 minutes
ULORT0	Upstream Lane Occupancy Ratio (30-Sec)	ULORT0 = ULOMX0 / ULOMN0
ULORT1	Upstream Lane Occupancy Ratio (1-Min)	ULORT1 = ULOMX1 / ULOMN1
ULORT5	Upstream Lane Occupancy Ratio (5-Min)	ULORT0 = ULOMX5 / ULOMN5
ULSDF0	Upstream Lane Speed Difference (30-Sec)	ULSDF0 = ULSMX0 - ULSMN0
ULSDF1	Upstream Lane Speed Difference (1-Min)	ULSDF1 = ULSMX1 - ULSMN1
ULSDF5	Upstream Lane Speed Difference (5-Min)	ULSDF5 = ULSMX5 - ULSMN5
ULSMN0	Upstream Lane Speed Minimum (30-Sec)	Minimum speed of station's constituent sensors over the last 30 seconds
ULSMN1	Upstream Lane Speed Minimum (1-Min)	Minimum speed of station's constituent sensors over the last 1 minute
ULSMN5	Upstream Lane Speed Minimum (5-Min)	Minimum speed of station's constituent sensors over the last 5 minutes
ULSMX0	Upstream Lane Speed Maximum	Maximum speed of station's

Name	Decsription	Definition
	(30-Sec)	constituent sensors over the last 30 seconds
ULSMX 1	Upstream Lane Speed Maximum (l-Min)	Maximum speed of station's constituent sensors over the last 1 minute
ULSMX5	Upstream Lane Speed Maximum (5-Min)	Maximum speed of station's constituent sensors over the last 5 minutes
ULSRTO	Upstream Lane Speed Ratio (30-Sec)	ULSRTO = ULSMXO / ULSMNO
ULSRTl	Upstream Lane Speed Ratio (1-Min)	ULSRTl = ULSMX 1 / ULSMN 1
ULSRT5	Upstream Lane Speed Ratio (5-Min)	ULSRT5 = ULSMX5 / ULSMN5
ULVDFO	Upstream Lane Volume Difference (30-Sec)	ULVDFO = ULVMXO - ULVMNO
ULVDFI	Upstream Lane Volume Difference (1-Min)	ULVDFl = ULVMXl-ULVMN 1
ULVDF5	Upstream Lane Volume Difference (5-Min)	ULVDF5 = ULVMX5 - ULVMN5
ULVMNO	Upstream Lane Volume Minimum **(30-Sec)**	Minimum volume of station's constituent sensors over the last 30 seconds
ULVMN 1	Upstream Lane Volume Minimum (1 -Min)	Minimum volume of station's constituent sensors over the last 1 minute
ULVMN5	Upstream Lane Volume Minimum (5'-Min)	Minimum volume of station's constituent sensors over the last 5 minutes
ULVMXO	Upstream Lane Volume Maximum (30-Sec)	Maximum volume of station's constituent sensors over the last 30 seconds
ULVMX 1	Upstream Lane Volume Maximum (1-Min)	Maximum volume of station's constituent sensors over the last 1 minute
ULVMXS	Upstream Lane Volume Maximum (5-Min)	Maximum volume of station's constituent sensors over the last 5 minutes
ULVRT0	Upstream Lane Volume Ratio (30-Sec)	ULVRTO = ULVMXO / ULVMNO
ULVRT1	Upstream Lane Volume Ratio (l-Min)	ULVRT I= ULVMX 1/ ULVMN 1
ULVRT5	Uustream Lane Volume Ratio (5-	ULVRT5 = ULVMX5 /

Name	Decsription	Definition
	Min)	ULVMN5
UODDT1	Upstream Occupancy First Derivative (1-Min)	Rate of change in OCCUP1 over last 1 minute
UOD2DT1	Upstream Occupancy Second Derivative (1-Min)	Rate of change in UODDT1 over last 1 minute
USPDTD1	Upstream Speed Temporal Difference (1-Min)	1.0 - (SPDUP1[t] / SPDUP1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
UVDDT1	Upstream Volume First Derivative (1-Min)	Rate of change in VOLUP1 over last 1 minute
UVD2DT1	Upstream Volume Second Derivative (1-Min)	Rate of change in UVDDT1 over last 1 minute
UVOLTD1	Upstream Volume Temporal Difference (1-Min)	1.0 - (VOLUP1[t] / VOLUP1[t-2]), where "t" is the current time and "t-2" is two minutes prior to the current time
VOLDN0	Volume Downstream (30-Sec)	Number of vehicles passing downstream detector station
VOLDN1	Volume Downstream (1-Min)	Number of vehicles passing downstream detector station
VOLDN5	Volume Downstream (5-Min)	Number of vehicles passing downstream detector station
VOLFDN0	Volume Filtered Downstream (30-Sec)	Kalman filtered value of VOLDN0
VOLFUP0	Volume Filtered Upstream (30-Sec)	Kalman filtered value of VOLUP0
VOLSDF0	Volume Spatial Difference (30-Sec)	VOLSDF0 = VOLUP0 - VOLDN0
VOLSDF1	Volume Spatial Difference (1-Min)	VOLSDF1 = VOLUP1 - VOLDN1
VOLSDF5	Volume Spatial Difference (5-Min)	VOLSDF5 = VOLUP5 - VOLDN5
VOLSDR0	Volume Spatial Difference Relative (30-Sec)	VOLSDR0 = VOLSDF0 / VOLUP0
VOLSDR1	Volume Spatial Difference Relative (1-Min)	VOLSDR1 = VOLSDF1 / VOLUP1
VOLSDR5	Volume Spatial Difference Relative (5-Min)	VOLSDR5 = VOLSDF5 / VOLUP5

Name	Decsription	Definition
VOLSRT0	Volume Spatial Ratio (30-Sec)	VOLSRT0 = VOLUP0 / VOLDN0
VOLSRT1	Volume Spatial Ratio (1-Min)	VOLSRT1 = VOLUP1 / VOLDN1
VOLSRT5	Volume Spatial Ratio (5-Min)	VOLSRT5 = VOLUP5 / VOLDN5
VOLUP0	Volume Upstream (30-Sec)	Number of vehicles passing upstream detector station
VOLUP1	Volume Upstream (1-Min)	Number of vehicles passing upstream detector station
VOLUP5	Volume Upstream (5-Min)	Number of vehicles passing upstream detector station